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Vehicle crash simulations for safety: Introduction of connected and automated vehicles on the roadways

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ABSTRACT

Traffic accidents are one main cause of human fatalities in modern society. With the fast development of connected and autonomous vehicles (CAVs), there comes both challenges and opportunities in improving traffic safety on the roads. While on-road tests are limited due to their high cost and hardware requirements, simulation has been widely used to study traffic safety. To make the simulation as realistic as possible, real-world crash data such as crash reports could be leveraged in the creation of the simulation. In addition, to enable such simulations to capture the complexity of traffic, especially when both CAVs and human-driven vehicles co-exist on the road, careful consideration needs to be given to the depiction of human behaviors and control algorithms of CAVs and their interactions. In this paper, the authors reviewed literature that is closely related to crash analysis based on crash reports and to simulation of mixed traffic when CAVs and human-driven vehicles co-exist, for studying traffic safety. Three main aspects are examined based on our literature review: data source, simulation methods, and human factors. It was found that there is an abundance of research in the respective areas, namely, crash report analysis, crash simulation studies (including vehicle simulation, traffic simulation, and driving simulation), and human factors. However, there is a lack of integration between them. Future research is recommended to integrate and leverage different state-of-the-art transportation-related technologies to contribute to road safety by developing an all-in-one-step crash analysis system.

1. Introduction

Traffic accidents are one main cause of human fatalities in modern society. For example, from 2000 to 2018, the road traffic deaths rose from 1.15 million to 1.35 million per year world -wide (Chang et al., 2020, World Health Organization, 2021). With the fast development of connected and autonomous vehicles (CAVs), there comes a great opportunity to improve traffic safety because CAVs can be more reliable, predictable, and safer (Ye and Yamamoto, 2019, Campisi et al., 2021). However, the introduction of CAVs into the traffic network is bound to be a gradual process instead of a sudden change, and there will be a transition period during which CAVs and human-driven vehicles coexist on the road (Xu et al., 2021, Chen et al., 2021a, Ma et al., 2022). This transition period needs to be carefully analyzed and planned to enable safe and efficient interactions between CAVs and human-driven vehicles. To support such analysis, on-road testing has been conducted, including, for example, the CAVs' predictive cruise control analysis using machine learning methods in the state of Georgia (Gao et al., 2019), factor analysis (e.g., CAV driving mode, and collision location) regarding severity level of CAV involved crashes using descriptive statistics analysis method in the state of California (Xu et al., 2019), driverless pizza delivery in the state of Michigan (Snavely, 2017), and the Uber self-driving car test in the state of Arizona (Tech AZ, 2019). Although such tests are useful for accumulating knowledge and understanding about behaviors of CAVs in mixed traffic, they are not sufficient to study potential crash scenarios systematically due to the sparsity of accident data.

To address that limitation, traffic simulations can be used to investigate potential risks and crash scenarios. One main challenge, however, is how to accurately introduce human factors into such simulations so that there will not be a gap between simulation results and the corresponding actual roadway scenarios. To start, the authors conducted a

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comprehensive survey that revealed roundabout is one of the tricky road geometries where the introduction of CAVs may increase maneuver challenges for human drivers (Hung et al., 2022). This survey pointed out the importance of road infrastructure itself in addition to vehicles and human factors in traffic safety, which appears to have less investigation compared to the other two aspects. Therefore, in this paper, we focus on the simulation environments for mixed traffic conditions with consideration of road infrastructure. Literature has been searched and reviewed under three subtopics: data source, simulation methods, and human behavior. For data source, we concentrated on crash reports, which offer valuable real-world crash data that can be used to inform traffic simulation studies. For simulation methods, we explored microscopic traffic simulation, vehicle simulation and driving simulation. For human behavior, our review was guided by information-processing limitations of drivers in general – including those caused by distraction, limited attention and working memory capacity, and inaccurate hazard perception – as well as risk factors for individual drivers that affect driver behavior. The overarching goal was to determine the state of the art and existing gaps in successfully simulating driving scenarios in mixed traffic conditions with road infrastructure integrated.

2. Review methodology

We adopted a four-step review methodology: (1) database selection, (2) literature retrieval, (3) categorization, and (4) information analysis. In Step (1), we selected Scopus, American Society of Civil Engineers (ASCE) Library, ProQuest, and Google Scholar as the databases from which to search literature. In Step (2) literature retrieval, we used the following keywords and their combinations: crash analysis, crash simulation, vehicle simulation, traffic simulation, human factors, driving simulator, roundabout, and crash reconstruction. In Step (3) categorization, the title and abstract of each publication retrieved were manually checked. Three broad subtopics were identified – crash analysis, simulation method, and human behavior, and it was decided whether to include each paper based on whether useful information was found related to at least one of the subtopics. The supportive techniques/methods under each subtopic (e.g., simulation method) were explored to further analyze the research topic. Aspects of human behavior (e.g., affective factors) were considered because they are essential to safe interaction between CAVs and HDVs. In Step (4) information analysis, the selected papers were reviewed in detail and analyzed in the context of our research goal.

2.1. Step 1 database selection

In this paper, we provide a review of the literature related to traffic crashes, including crash analysis, crash simulation, human factors, and state-of-the-art technologies. Therefore, multiple database/literature resources were selected to identify which works to review. The Scopus, ASCE Library, ProQuest, and Google Scholar databases were selected, because they are accessible to web search engines that provide the title, abstract, and/or full text of the retrieved articles. The above-mentioned databases helped support the scope of the review in this paper.

2.2. Step 2 literature retrieval

After defining the database, key words were developed and used based on the review scope to search the related literature in the database. They included traffic simulation, driving simulator, roundabout, crash simulation, human factors, crash reconstruction, and crash analysis. The literatures on these topics were selected from peer-reviewed journals and conference proceedings, such as *Accident Analysis & Prevention*, *Simulation Modelling Practice and Theory*, *Journal of Clinical and Experimental Neuropsychology*, and *Road Safety on Five Continents Conference*.

2.3. Step 3 categorization

In this step, three subtopics were defined and selected based on the purpose of this review paper: crash analysis, simulation method, and human behavior. After searching the literatures using the developed key words, we manually categorized the literature on each subtopic and conducted literature reviews accordingly.

2.4. Step 4 information analysis

In the final step, we reviewed the selected literatures using developed key words from the selected database. The goal was to comprehensively review the vehicle crash and crash simulation areas, including cutting-edge technologies, as well as human factors issues related to crashes, in order to contribute to transportation safety research. The construction of this paper is organized accordingly as detailed in the following sections.

3. Crash analysis

3.1. Data source

In terms of crash analysis, the first step is to identify the types of data sources, that could be used to support further research including crash simulation and human factor analysis. The identified sources are summarized in Table 1 in the order covered in the text. Koch et al. (2021) analyzed data from National Highway Traffic Safety Administration (NHTSA)'s 2016–2018 *Crash Report Sampling System* (CRSS) database, including a nationwide sample of vehicle–pedestrian crashes, to compare pedestrian injury severity. Video data provide more accurate, rich, and synchronized traffic information with all relevant vehicles on the road than do crash reports if they are available. Kolla et al. (2022) developed a method for in-depth reconstruction of traffic crashes using video footage from vehicle cameras based on the fusion of kinetic trajectory simulation. The developed method was also applied to the

Table 1
Illustration of related literatures.

Publication	Data Source	Method	Outcome
(Koch et al., 2021)	*Crash Report Sampling System* (CRSS) database of NHTSA between 2016 and 2018	Logit models are developed using seven independent variables, including "weather, lighting condition, speed limit, speeding violation, vehicle body type, driver impairment, and pedestrian age"	Compare pedestrian injury factors between intersections and non-intersection locations
(Kolla et al., 2022)	Video footage from vehicle cameras	Fusion of kinetic trajectory simulation	Reconstruct in-depth traffic crashes
(Aldimirov and Arnaudov, 2018)	Event data recorder (EDR) data (i.e., GPS/INS data)	Kalman filter that is similar to inertial navigation	Reconstruct cars' paths from crashes automatically
(Bao et al., 2019)	Structured data (i.e., digital data) and unstructured data (i.e., textual data), including multiple datasets including "crash data, large-scale taxi GPS data, road network attributes, land use features, population data and weather data"	Spatiotemporal deep learning method	Explore the contribution of deep learning approach to citywide short-term crash risk prediction

reconstruction of real-world traffic incidents, which showed detailed information at each time frame for each vehicle such as speed, distance traveled, acceleration, and yaw rate/angle. The results showed that typical urban traffic incidents with pre-collision durations of 2 to 3 s can be reconstructed in approximately three days. Aldimirov and Arnaudov (2018) proposed a method for automatic reconstruction of cars' paths from crashes using event data recorder (EDR) data. In practice, the method can support creating expert reports for crash investigation. Bao et al. (2019) used machine learning methods to analyze multiple datasets including "crash data, large-scale taxi GPS data, road network attributes, land use features, population data and weather data". In general, the data sources could be categorized into structured data (i.e., digital data) and unstructured data (i.e., textual data).

3.2. Analysis method

Transportation research has been one of the popular topics in civil engineering during the past four decades. It is essential for researchers to identify issues in road safety (e.g., crashes) and develop roadmaps to address the issues effectively (Yan et al., 2008, Zhang et al., 2016, Kwayu et al., 2019). Therefore, CAVs are being developed with a goal of reducing traffic accidents. However, many safety issues between automation and human drivers remain, as well as those between automation and transportation systems (Alambeigi et al., 2020, Feng et al., 2023). Consequently, in this paper, we review relevant studies in the literatures and summarize road safety issues that need to be considered from both drivers' and non-drivers' perspectives. To be specific, to better understand the mechanisms of CAVs and to leverage CAV-related technologies to contribute to the transportation domain from the drivers' and non-drivers' perspectives, researchers must put effort into collecting, analyzing, processing, and exploiting crash data (e.g., reports) to support transportation research. Accordingly, some researchers have analyzed crash reports to understand the mechanisms underlying car crashes and developed automated tools to aid crash analysis.

One example is the work of Zhang et al. (2021b) in support of crash-report sampling. They noted that non-fatal variance estimates are often made using a composite estimator that combines estimates from the Fatality Analysis Reporting System (FARS, an annual census of fatal motor vehicle traffic accidents) with non-fatal crash estimates from the Crash Report Sampling System (CRSS, an annual probability sample of all police-reported fatal and non-fatal traffic crashes). However, they pointed out that the standard error estimation of the composite estimator becomes complicated when there is nonlinearity in the FARS and CRSS estimates. To remedy this problem, Zhang et al. (2021b) developed and justified a variance estimation method using all sampled CRSS crashes (fatal or non-fatal). They concluded that the composite estimator produces better injury-related total estimates. Zhang et al. (2021b) provided programs in SAS, SUDAAN, and R software to calculate the estimates automatically.

Similarly, Nie et al. (2021) developed a web-based compliance-checking tool to automatically map and label missing elements of crash reports to better align with the federal Model Minimum Uniform Crash Criteria (MMUCC; National Highway Traffic Safety Administration, 2017). The purpose of the tool was to manage crash data in a more uniform manner across states and simplify the crash report workflow by maintaining high quality crash data in a state's workflow. The compliance-checking tool developed by Nie et al. (2021) can be used to calculate a compliance score based on mean element scores using formulas provided by the Governors Highway Safety Association (GHSA). After developing the tool, Nie et al. (2021) then analyzed crash data workflows at Alabama and Wisconsin and applied their compliance checking tool to evaluate one crash report from each state. Based on such evaluations, recommendations were made in best practices of crash data workflows. In spite of the automation enabled by the compliance checking tool, Nie et al. (2021) concluded that manual quality assurance and quality control is still preferred for determining if the crash narrative parts of the crash report are adequate.

Nie et al. (2021) were not alone in identifying the challenges in automating the analysis and processing of the narrative part of crash reports; natural language processing and machine learning techniques have been commonly resorted to in dealing with such challenges. For example, Boggs et al. (2020) developed a text analytics and hierarchical Bayesian heterogeneity-based approach to analyze traffic collision reports from the California Department of Motor Vehicles to contribute to interactions of AVs and HDVs in complex urban environments. Through the help of such analysis, Boggs et al. (2020) were able to discover that the likelihood of rear-end crash was significantly higher with (1) automated driving system's engagement and (2) in mixed land-use settings. Likewise, Kutela et al. (2022a) leveraged Bayesian networks to analyze 333 AV crash reports in California to understand the associated factors of vehicle at fault, collision type, and injury outcome, as three interrelated outcome variables for AV involved clashes. Note that the data (e.g., crash time, crash location, CV & AV directional movement, and driving mode type during collision) were manually extracted from crash reports in Kutela et al. (2022a). In parallel and in comparison, Kutela et al. (2022b) analyzed crash narratives data from California between 2017 and 2020, leveraging text network analysis (TNA) (i.e., an unsupervised text mining approach) and machine learning classifiers. In the work of Kutela et al. (2022b), four classic machine learning classifiers were tested including Support Vector Machines (SVMs), Naïve Bayes (NB), Random Forest (RF), and Neural Networks (NNs). With the help of TNA and machine learning algorithms, Kutela et al. (2022b) discovered positive correlations between autonomous mode of AVs and crashes that indirectly involve vulnerable road users (VRUs), and further identified key predictors of the VRUs-AV related crashes: "crosswalks, intersections, traffic signals, movements of AVs (turning, slowing down, stopping)".

In a related study, Das et al. (2020) obtained the AV-related collision reports (of different manufacturers) in California (September 2014 to May 2019) and leveraged Bayesian latent class models to analyze the reports into clusters (of collision patterns); they furthermore gathered police collision narratives to perform text mining. Through clustering Das et al. (2020) identified six classes of collision patterns based on different variables (i.e., collision type, damage to the vehicle, operator injury severity, lighting conditions, the number of vehicles involved, weather conditions, the event prior to the collision, and whether the vehicle was moving or stopped) and collision traits (i.e., "turning, multi-vehicle collisions, dark lighting conditions with streetlights, and sideswipe and rear-end collisions"). A positive correlation was found between autonomous mode of AVs and the likelihood of adverse weather collision. Through text mining, it was determined that current narrative structure in crash reports is insufficient and needs to be improved to better support the investigation of automation levels and collision likelihood. In summary, crash reports analysis has been instrumental in investigating traffic safety including implications of CAVs. In spite of the many discoveries in the associations (usually positive) between autonomous mode and crash likelihood through such analysis, the research community wants richer and better structured crash reports to support deeper analysis in such vein.

From drivers' perspective in terms of leveraging crash data sources (e.g., reports), some researchers analyzed human behaviors that are reflected in the crash to better support traffic accident analysis. Hsiao et al. (2018) conducted a literature review regarding current knowledge and challenges related to emergency vehicle crashes and the major contributing risk factors. The risk factors fell into four categories: driver, task, vehicle, and environmental factors. Shaon et al. (2019) used a crash prediction model (i.e., multivariate multiple risk source regression model) to identify the correlation between severity levels of crash counts and the crash contributing factors from different crash sources. Also, Bucsuházy et al. (2020) explored human behaviors and conducted individual interviews with traffic accident participants to identify the causes of accidents. Their study considered all relevant information, including physical and mental conditions, driving practices and habits, and sociodemographic characteristics of the drivers. All of the above-mentioned studies demonstrate that drivers play an important role that needs to be considered for traffic crash analysis.

From non-drivers' perspective, some researchers studied roadway infrastructure and roadway safety conditions to explore non-driver factors that affect traffic crashes. For example, Papadimitriou et al. (2019) assessed infrastructure-related risk factors to classify them into three categories: risky, probably risky, and unclear. This study analyzed 59 specific risk factors, including "alignment features (e.g., horizontal-vertical alighment deficiencies), cross-section characteristics (e.g., superelevation, lanes, median and shoulder deficiencies), road surface deficiencies, workzones, junction deficiencies (interchange and at-grade) etc.". Similarly, Merlin et al. (2020) reviewed various built environment types to explore whether a consistent relationship exists between built environment measures and crash frequency. The results demonstrated that there are mixed positive and negative correlations or completely negative correlations between many built environment measures (e.g., density, and land uses) and crash frequency. Thus, there are a lot of unsafe issues/factors from the infrastructure side that need to be incorporated into traffic crash analysis research.

To develop corresponding analysis methods (e.g., crash simulation) to support transportation research from drivers' perspective, some researchers have focused on developing driving simulators to help identify the factors/parameters of crashes. For example, Li et al. (2019) used a high-fidelity driving simulator (i.e., Beijing Jiaotong University driving simulator) to study drivers' collision avoidance performance. The study results demonstrated that braking is the most common response, along with turning, to avoid head-on collisions and pedestrian collisions. Erkuş and Özkan (2019) used a driving simulator (i.e., STISIM Driver Model 100 Wide Field-of-View Complete System with the STISIM DRIVE-M100W-ASPT software) and hierarchical regression analysis to investigate the relation between driving skills and driver behaviors of young male drivers. The results illustrated a positive relation between safety skills and perceptual motor skills of young male drivers and their speeds, and overtaking behaviors. Gaweesh et al. (2021) conducted driving simulation to explore the effects of connected vehicle (CV) distress and re-routing technology to reduce secondary crashes. They found that the CVs could reduce operating speed and speed variation to enhance commercial truck driving behaviors; in addition, all the participants could avoid secondary crashes under a CV environment.

Similarly, McGehee et al. (2000) conducted two experiments of driver performance and reaction in a scenario of intersection incursion crash, one on the Iowa Driving Simulator and another during an actual driving experiment on a test track. Total brake reaction time and time to initial steering in the simulated and real driving were equivalent. This outcome suggests that crash avoidance results in simulated driving can be generalized to a real-world driving environment. From non-drivers' perspective, some researchers put their efforts into generating traffic simulations to identify the factors that affect traffic safety. For example, Hou and Chen (2020) developed a framework to analyze traffic safety in work zones under adverse conditions, which considered weather, road surface conditions, and specific work zone configurations. The results showed that adverse weather conditions increase the crash risk in work zones. Correspondingly, Zhang et al. (2021a) used the surrogate safety assessment model (SSAM) to estimate the safety benefits in a freeway crash hotspot in Wuhan for differential penetration-rate analysis of CAVs. The study illustrated that there is no significant improvement in the safety factors (e.g., conflicts, acceleration, and velocity difference) when the penetration rate of CAVs is less than 50%.

4. Crash simulation

Three types of crash-related simulations were reviewed: vehicle simulation, traffic simulation, and driving simulation. Vehicle simulations typically involve reconstructions of crash scenes to capture the actions of the individual vehicles that were involved. Traffic simulation is the modeling of transportation systems, for example, the flow of vehicles at a roundabout. Driving simulations incorporate the actions of humans performing in a driving simulator or models of the humans to include relevant human characteristics.

4.1. Vehicle simulation

It is challenging to evaluate CAVs because crashes are rare events and data associated with crashes are limited. Besides, all the scenarios are predefined for testing CAVs. Although good performance of CAVs can be achieved through these predetermined test scenarios, naturalistic scenarios are more complicated and harder to predict. This limitation means that the test results from predefined test scenarios may not be valid for everyday driving (Alghodhaifi and Lakshmanan, 2021). Therefore, vehicle simulation of CAVs and reconstruction of crash scenes to find out the cause of incidents are vital to evaluate the reliability and safety issues associated with CAVs.

4.1.1. Safety impact of driving behavior on CAVs

According to Stutts et al. (2003), human distractions account for 30% of crashes in the U.S. recorded in crash reports. Typical distraction behaviors while driving include cell phone usage, shaving, applying makeup, eating, and drinking. However, no current driving simulation software incorporates the consideration of such distractions or other reckless driving behavior. Astarita and Giofré (2019) proposed a new methodology for considering driver error (e.g., being occupied by mobile calls or momentarily distracted due to psychological or physical issues) in traffic simulation environments such as VISSIM, Advanced Interactive Microscopic Simulator for Urban and Non-urban Networks (AIMSUN), and Tritone. The method introduced traffic conflict indicators such as the angle of the deviated trajectory and distraction time duration. The proposed methodology can be applied for evaluating resulting potential crashes, as well as the safety impact of CAVs.

4.1.2. Pre-crash velocity and vehicle condition

A goal of vehicle crash reconstruction is to determine the velocity, angles, and related factors prior to impact. Elastic–plastic deformation of the vehicles is one source of information generated as a consequence of a crash. However, the deformation data must be analyzed to generate estimates of the relevant parameters prior to the accident. Zhang et al. (2008) used NNs for mapping the relations between the initial crash velocity parameter and deformation. They validated the procedure by applying it to a typical traffic accident. More recently, Chen et al. (2021b) developed a machine learning algorithm to identify a broader range of initial impact parameters (i.e., offset, angle and velocity) of vehicle crashes based on its final material damage condition and permanently deformed structure configuration. The vehicle crash inverse solution of pre-crash data was determined by leveraging plastic deformation signature with high accuracy. The algorithm was tested on 8 test cases based on a small 320 neuron deep learning model, which resulted in maximum error of 11.76% on offset prediction, 22.41% on angle prediction, and 8.49% on velocity prediction. The authors also pointed out significant improvement can be made by increasing the neuron number. The main advantage of the proposed method is that accurate pre-crash data can be retrieved by carrying out simple measurement of residual permanent deformation of crashed cars in the crash site.

4.2. Traffic simulation

As noted, traffic simulation refers to the modeling of transportation systems, typically at specific problematic areas. One such area is the roundabout intersection.

4.2.1. Conflict and crash simulations with analysis at roundabouts

As a form of intersection control, roundabouts are becoming increasingly common in the US due to their superior safety performance (Al-Ghandour et al., 2022). Compared with intersections, roundabouts reduce speeds for safer following, avoid lockups, increase capacity, reduce the number of conflict points, eliminate conflict types, and reduce crash severity (Flannery and Datta, 1996, Mandavilli et al., 2009, Daniels et al., 2011). Because of these advantages, roundabouts reduce the number of crashes with injuries or fatalities (e.g., Flannery and Datta, 1996, Persaud et al., 2000, Retting et al., 2001, Elvik, 2003). In spite of roundabouts' positive impact on reducing crash frequency and severity when compared with traditional intersections, they cannot totally prevent crashes (Mandavilli et al., 2009). Based on Mandavilli et al.'s (2009) research, there are four main crash types within roundabouts: "run-off-road, rear-end, sideswipe, and entering-circulating". It is essential to understand how these distinct types of crashes occur, and how to predict crashes and develop countermeasures to enhance traffic safety in and near roundabouts (Mandavilli et al., 2009).

Traffic simulation was introduced in research to evaluate the performance of transportation networks as well as emerging technologies such as CAVs. Since then, microscopic traffic simulation (i.e., simulating individual vehicles and their behaviors) has been considered an effective method to analyze traffic performance, which would model individual vehicle behaviors and their interactions (Astarita and Giofré, 2019). In addition, new technologies such as connected vehicles and autonomous vehicles have been applied to traffic simulations (Astarita et al., 2017, Deluka et al., 2018). There is a large body of literature in microscopic traffic simulation. In this section, we mainly reviewed studies that are related to simulating roundabouts.

Crashes. Zheng et al. (2010) analyzed roundabout crash patterns and used these patterns to compare between roundabout categories and between at-fault driver residency types (local-city or outside-city driver). In addition, they quantified 12 types of inappropriate negotiations based on the crash patterns. Their findings showed that entering-circulating type of crash was the severest at single-lane roundabouts, whereas the sideswipe crash showed a higher percentage at multi-lane roundabouts because most sideswipes happened between circulating vehicles. In addition, Polders et al. (2015) identified dominant crash types at roundabouts by considering the crash location, which was rarely considered in the prior studies. They collected and sampled crashes at roundabouts from police reports in Flanders, Belgium. Four dominant crash types were identified which included rear end, collisions with VRUs (e.g., cyclists, moped riders), entering–circulating, and single-vehicle collisions with the central island. The results showed that more crashes occurred in the entering lanes than in the exiting lanes (Polders et al., 2015).

Conflicts. More studies have been conducted to analyze conflicts at roundabouts rather than crashes. The definition of traffic conflict is "an observable event which would end in an accident unless one of the involved parties slows down, changes lanes, or accelerates to avoid collision" (Jin et al., 2021, Risser, 1985). There are several main reasons to analyze conflicts rather than crashes. First, the crashes have a rare probability of happening compared with conflicts. Second, Dijkstra et al. (2010) showed that using conflicts to predict the number of crashes and examining the possibility of a relationship between calculated conflicts at junctions in the model would be possible. He recorded crashes by using microsimulation models which indicates that the number of simulated conflicts and observed crashes follows a Poisson log-linear distribution (Al-Ghandour, 2011). Third, both crashes and traffic conflicts are not intentional, and they have the same cause (e.g., some sort of failure). Therefore, crashes will decrease if traffic conflicts are reduced, which suggests that both conflicts and crashes are useful for safety evaluation and management.

Combining the analysis of conflicts and crashes, McIntosh et al. (2011) did an analysis of the roundabouts in Michigan to evaluate the crash data both before and after their construction using naïve method and Empirical Bayes (EB) analysis. Although the naïve method cannot be accounted for by the significant time trend, it is consistent with the EB results in general. Moreover, comparing the severity of the crashes before and after the roundabout construction, they found that more than 20% of the crashes resulted in an injury or fatality in the "before" period while that number was slightly over 10% in the "after" period. After constructing the roundabout, the following two results showed that the "after" construction period had a significant effect compared with the "before" period. First, the crash types that often result in the severest crashes (angle, head-on, head-on left turn, pedestrian, and bicycles) were reduced substantially. Second, over 10% of angle crashes were reduced after the roundabout construction.

Vehicle movements. Other researchers have used traffic simulation to replace observations to model vehicle movements (Minderhoud and Bovy, 2001). In addition, compared with methods that estimate conflicts from video data, micro-simulation is an easier and faster method to create conflicts by using traffic conflict models and evaluating collisions (Saulino et al., 2015). To quantitatively assess the safety level, surrogate safety assessment model (SSAM) software was developed to combine microsimulation models and automated conflict analysis (Office of Safety Research and Development, 2003). SSAM is "developed to automatically identify, classify, and evaluate traffic conflicts in the vehicle trajectory data output from microscopic traffic simulation models" (U.S. DOT FHWA, 2022). It also has built-in statistical analysis functions (e.g., for calculating conflict frequency and severity measures) that could help analysts in safe traffic infrastructure designs (Gettman et al., 2008, U.S. DOT FHWA, 2022). Specifically, visual analysis (e.g., "types of conflicts, conflicts areas, and conflict severities" (Al-Ghandour et al., 2011)) and trajectory information (e.g., vehicle position, vehicle speed, and vehicle acceleration) were processed by SSAM to determine the locations of the most serious conflicts and the associated types of conflicts, and to compare intersection design alternatives in terms of the locations of conflicts (Souleyrette and Hochstein, 2012). Virdi et al. (2019) proposed a method which uses incrementally transitioning of the fleet to CAVs (i.e., from low penetrations to high penetrations) and then assesses the safety performance via SSAM. The results showed that low CAV penetrations increased conflicts at signalized intersections but decreased them at priority-controlled intersections, while high CAV penetrations reduced conflicts globally. However, this study is limited in highway environment which did not consider the mixed urban and freeway environment.

Giuffrè et al. (2018) investigated roundabout safety performance with microsimulation to predict crash using peak hour conflicts. The estimation of traffic conflicts is conducted in the SSAM software for each roundabout using trajectory exported from simulation software (e.g., AIMSUN simulation, AI for intelligent mobility, and VISSIM). Crash data from 26 roundabouts were used to fit a generalized linear model for the prediction model (Giuffrè et al., 2018), which also showed a good fit by the cumulate residuals. In addition, (Saulino et al., 2015) investigated how simulated conflicts can be used as surrogate safety measures for roundabouts. The numbers of peak-hour conflicts at roundabout entries were estimated using VISSIM which was calibrated from roundabout data collected in the U.S. (Giuffrè et al., 2018). Results showed that simulated conflicts could be used as a surrogate measure due to the proper calibration for crash prediction models and conflicts prediction models.

4.2.2. Pre-crash studies

Pre-crash studies have the goal of identifying situations immediately prior to crashes. The pre-crash scenario that includes vehicle movements and critical scenarios analysis is used to describe time-to-collision based crash statistics and kinematic information in order to design vehicle-to-vehicle (V2V) communications-based countermeasures (Najm et al., 2013). There are three main pre-crash construction methods (Liu et al., 2021) including pre-crash data analysis (Davidse et al., 2019), clustering (Nitsche et al., 2017), and pre-crash scenario typology (Najm et al., 2007). The latter method is used to analyze crash scenarios according to contributing factors, which include the driving environment (e.g., clean weather, daylight) and road (e.g., geometry, dry surface), driver (e.g., age, gender, alcohol, drugs, fatigue), and vehicle (e.g., speed, usage years, weight) (Liu et al., 2021). More specifically, Davidse et al. (2019) analyzed the crashes, including contributing factors to crash occurrence and injuries. They identified the most common contributing factors per type of crash and provided alternative measures which tried to prevent these types of accidents for safety improvement in future. In addition, a clustering method was used to establish the basis for safety test of the Autonomous Driving System (ADS) by Nitsche et al. (2017) through identifying critical pre-crash scenarios at T- and four-legged intersections (Liu et al., 2021). Najm et al. (2007) defined a new typology that consists of 37 pre-crash scenarios based on the 2004 General Estimates System (GES) crash database "involving at least one light vehicle (i.e., passenger car, sports utility vehicle, van, minivan, or light pickup truck)" (Liu et al., 2021). "The goal of this typology is to establish a common vehicle safety research foundation for public and private organizations, which will allow researchers to determine which traffic safety issues should be of first priority to investigate and to develop concomitant crash avoidance systems" (Najm et al., 2007).

Although many practitioners and transportation engineers have been using microscopic simulation for different applications, few studies focused on quantifying the relationship (e.g., frequency, severity) between real crashes and simulated traffic conflicts at roundabouts by using microsimulation (Giuffrè et al., 2018). In addition, there is limited research focused on pre-crash simulation and analysis at roundabouts using real crash datasets. These knowledge gaps on the estimation of surrogate safety measures at roundabouts need to be filled (Giuffrè et al., 2018).

4.2.3. Single-vehicle crash simulation

Astarita et al. (2021) concluded that traffic simulation cannot predict single-vehicle crashes. The reason is that simulation tools such as AIMSUN and VISSIM depict traffic conflicts based on the assumption that the trajectories of two vehicles must intersect (Astarita and Giofré, 2019). All the frequently used traffic indicators (e.g., Time to Collision, Post-Encroachment Time) are based on this assumption so they are incomplete for accounting for single-vehicle crashes. For example, undivided highway safety cannot be evaluated in a simulation environment based on current conflict techniques unless driver error is introduced (Astarita and Giofré, 2019). Current conflict techniques do not take into account scenarios when road objects do not move on overlapping trajectories, which could lead to single-vehicle crashes (i.e., collisions with fixed objects) (Astarita et al., 2021). However, single-vehicle crashes consist of 19% of all reported crashes and result in 44% of fatal crashes overall in the US (Astarita and Giofré, 2019, Holdridge et al., 2005).

4.3. Driving simulation

Driving simulation is defined as enabling "the development of testable dynamic models of driving behavior and the evaluation of tactical skills (e.g., choice of speed and lane position) and operational vehicle control (e.g., steering and braking) as integrated performance measures that incorporate features of visual perception, memory, attention, and directed search in a face-valid driving-relevant context. (Michon, 1989, Ranney, 1994)" (Akinwuntan et al., 2012).

Driving simulators have been used for traffic safety studies since the turn of the century because of their advantages of easily producing diverse driving scenarios and collecting driving performance data under risky scenarios without placing drivers under actual risks of injuries or deaths (Bobermin and Ferreira, 2021). However, several issues also exist in the driving simulator studies. First, the traditional selection of risky scenarios for driving simulation relies on researchers' expertise (Bobermin and Ferreira, 2021), and their intuitions may not always be accurate. Therefore, the studies on discovering crash patterns from crash reports should be investigated to support the selection of risky traffic conditions. Also, leveraging the crash pattern discovery process can facilitate the automated processing of information from crash reports to driving simulation. Second, some studies argue traffic flow at current driving simulator is simple and this issue could be solved by integrating microscopic traffic simulation software into the driving simulator, which can generate more complex traffic flows. For example, previous study about testing drivers' performance at roundabouts used stable traffic flow (Azimian et al., 2021). The more complex traffic flow could be integrated into driving simulation software to improve the quality of driving simulation (Biurrun-Quel et al., 2017, Sun et al., 2015).

5. Human factors considerations

Although human factors are important for simulating roundabout crashes, little effort has been made to investigate specifically the influence of these factors in roundabout scenarios. Studies like those of Daniels et al. (2010) and Montella (2011) aimed to identify factors for predicting injury severity or accident rate in roundabouts instead of focusing on the special role of human cognitive or behavioral characteristics. Therefore, in this part, we broaden our discussion to include the general contribution of human factors to crash simulations in driving scenarios, but which would be likely to affect roundabout crashes in a similar manner.

In a crash or automobile accident, the people involved could be drivers, pedestrians, cyclists, or individuals riding scooters, skateboards, etc. The focus of the present paper is on simulations of accident scenarios for CAVs and human-driven vehicles, so our consideration of human factors emphasizes mainly drivers of vehicles. The majority of crash simulations use two methods to take driver factors into account: conducting crash simulations without participants or having real participants drive in simulated environments. In the former case, a driver behavior model is put into traffic simulations to imitate the driver's actions in a risky scenario (see Markkula et al., 2012, for a review). In the latter case, crash-related scenarios are used to test people's performance with manipulations of one or more driver factors (e.g., Bélanger et al., 2010, Bélanger et al., 2015). Before covering those topics, we provide a brief description of driving simulation.

5.1. Traffic simulations with driver behavior models

Driver behavior models are developed to capture near-crash driver behavior to investigate the relationship between driver reaction and safety. In general, without-participant simulations can provide a more controlled, repeatable, cheap, fast and safe measurement compared to obtaining data from naturalistic driving or driving simulators (Markkula et al., 2012). Recent development of driver behavior models has made it possible to make inferences at cognitive levels. Chai et al. (2017) proposed a Fuzzy Cellular Automata (FCA) model – a combination of fuzzy sets of linguistic terms and microscopic traffic behavior models – with the aim of simulating the misperception of vehicle gap and velocity. Based on the simulation results, driving performance and crash rate are found to be related to drivers' misperception. Moreover, this kind of cognitive failure (misperception) are more likely to cause driving errors in high volume traffic streams, which fits observations from naturalistic driving.

Driver behavior models can be improved by receiving input from with-participant simulator-based studies. For example, Habtemichael and de Picado Santos (2014) found that the crash risk of aggressive drivers relative to non-aggressive drivers is 3.1 to 5.9 times as great based on a microscopic traffic simulation approach. Aggressive driving was simulated by adjusting the parameters of the corresponding vehicles based on previous research of aggressive drivers. The study also found that aggressive driving can only save 1 to 2% of travel time in both non-congested and congested traffic conditions, but with the same high crash risk. One major limitation of this study is the lack of interaction between aggressive drivers and regular ones. In contrast, Park et al. (2019) first obtained behavioral data from a multi-agent driving simulation facility, where input from two driving simulators was integrated into the same traffic space to simulate the interaction between drivers when one of them behaved aggressively. Then the behavioral data were used to modify driving behavior parameters of the microscopic traffic simulation model in VISSIM. Results from VISSIM indicated that aggressive driving had a negative impact on both traffic safety and travel speed. The modified version of the simulation model can also be used to predict other consequences of aggressive driving and could be informative to policy making activities. Alonso et al. (2012) focused on longitudinal driving and the effect of distraction caused by a visual and cognitive secondary task. They used a similar method to improve the driver behavior model in ISi-PADAS (Integrated human modelling and Simulation to support human error risk analysis of Partially Autonomous Driver Assistance System) by applying the data obtained from driving simulators. With this input, the ISi-PADAS system is able to simulate the effect of distraction on driving activity and overall traffic safety. Alonso et al. (2012) focused on longitudinal driving and the effect of distraction caused by a visual and cognitive secondary task. They used a similar method to improve the driver behavior model in ISi-PADAS by applying the data obtained from driving simulators. With this input, the ISi-PADAS system is able to simulate the effect of distraction on driving activity and overall traffic safety.

Driving simulation studies can also further improve traffic simulation studies by providing calibrated parameters of the car following behavior for traffic flow analysis. The driving simulation study collects drivers' driving performance such as acceleration and distance to the lead car, which can be used to calibrate a car-following model. The calibrated car-following model could be imported into microscopic traffic simulations to investigate the impact on traffic flow. For example, a driving simulator study was carried out to collect drivers' performance under adverse weather conditions, and the Wiedemann 99 model was calibrated for VISSIM traffic simulation (Chen et al., 2019). In another study, driving behavior data were collected in a driving simulator study under snowy weather. The car-following model was calibrated by collected driving performance data, and the calibrated model was imported into VISSIM to investigate connected vehicle impacts on traffic safety (Yang et al., 2020).

However, as mentioned by Markkula et al. (2012), the current versions of the driver behavior model are far from their optimal form. Factors like alcohol, stress, and fatigue are still difficult to integrate into the simulation, not to mention the higher levels of the driver's cognitive processes (e.g., problem solving and decision making). Also, more research is still needed to focus on how to integrate the interaction between pre-crash scenarios and driving behaviors into the simulation. Since all these factors have been somewhat investigated in with-participant studies, the next step for improving traffic and crash simulation is still seeking methods of combining with- and without-participant research. In other words, one can only find a way to improve human behavior simulation through the direct investigation of human behaviors in specific contexts. Because roundabouts are complex driving environments for both humans and CAVs, they provide an ideal context for such investigation.

5.2. Human factors considerations in with-participant simulation studies

Unlike driver behavior models, which are typically used in traffic simulations, driving simulation research puts human participants into simulated traffic scenarios. By manipulating critical factors related to driving safety, behaviors from human drivers can be tested and measured with the aim of investigating limitations of human cognition. How the drivers interact with other vehicles and with environmental and infrastructural elements can be examined. The number of studies using roundabout scenarios is limited. Therefore, we cover those in the first subsection and focus the remaining subsections on other relevant factors studied using scenarios other than roundabouts but that are relevant to CAV-HDV interactions.

Driving simulation studies at roundabouts. Navigating within roundabouts is an intricate task which requires driver-car interactions and circulatory geometry (Azimian et al., 2021). Consequently, as noted, there are few studies specifically of drivers' performance at roundabouts. Azimian et al. (2021) tested 45 drivers under distracted and non-distracted conditions at roundabouts. The results showed that drivers were less careful, and more effort was needed to keep their attention, when driving under distracted conditions. Another study tested effects of different warning sounds as countermeasures to reduce drivers' speeds at roundabouts, and the results showed that a continuous pitch was the most effective (Rossi et al., 2013).

Distraction. A widely researched topic in with-participant simulation studies is the effect of distraction. Distraction can be internal or external. An internal distraction refers to the state of mind wandering – paying attention to task-irrelevant thoughts rather than the ongoing task. An on-road study by Burdett et al. (2019) had a researcher accompany 25 drivers in a 25-km route and ask them whether they were focusing on driving or thinking about something else at 15 predetermined road sections. The frequencies of the reported mind wandering correlated with the reported crashes' frequencies along the same route over a five-year period. Burdett et al. (2016), based on a survey of more than 500 participants, and Burdett et al. (2019) reported that mind wandering happens most often at slower, quieter, less complex or more familiar road sections. He et al. (2011) and Yanko & Spalek (2014) described simulation-based studies in which the participants performed car following in a high-fidelity driving simulator. In He et al.'s study, the participants were asked to report anytime they were aware of mind wandering, whereas in Yanko & Spalek's experiment, the participants were probed at randomly selected times to see whether they were focused on driving or mind-wandering. Both studies found evidence linking mind wandering to the potential risk of crashes. He et al. reported that mind wandering did not affect vehicle control but narrowed the focus of attention, whereas Yanko & Spalek reported that mind wandering was related to longer reaction times to sudden events, higher overall velocity, and a shorter headway distance. Those studies are good examples of ways to take internal distraction into account in simulation studies.

Like internal distraction, external distraction (e.g., cellphones or a sudden event) can also direct a driver's attention away from the road. Research has been conducted using driving simulators to investigate the effect of cell phones on crash risk. Li et al. (2016) tested participants with a rear-end collision task (responding to a leading vehicle's sudden deceleration) in a driving simulator across three cell-phone use conditions. Even though the people using cellphones took compensatory behaviors (e.g., slowing down), they still suffered from a higher risk of crashes. This difference in risk was not modulated by whether the cell phone was hands-free or hand-held, a finding that agrees with many studies evaluating cell-phone use (Caird et al., 2018). Alonso et al. (2012) had participants drive a simulator without a secondary task and while performing a visual or cognitive secondary task. The former required search of a series of visual displays for a target in each, identified by moving a gray indicator (similar to a cursor) to the half of the display in which it appeared, whereas the latter was counting backwards by 3 from a designated number. Participants reduced driving speed in both secondary-task conditions and allowed longer headways when approaching a vehicle when performing the cognitive secondary task but not the visual one.

Pawar and Patil (2018) reported that cellphone use made it more difficult for drivers to respond in time to other drivers' aggressive driving behaviors. Vollrath et al. (2021) showed that texting on a cellphone significantly impaired driving performance. This impairment was smaller for drivers who were more competent at texting on a cell phone than for less competent texters, although the subjective experiences were equally negative for both high and low competent groups. Lee et al.

(2018) focused on radio tuning while driving and found that the orienting of glance by this distraction task could be responsible for some avoidable crashes and the probability of crashing increased 2.8–5 times compared to a baseline driving condition. However, not all previous studies showed no potential benefit of a distraction in driving. Atchley and Chan (2011) found that requiring performance of an interactive verbal secondary task demanding comprehension and responding improved lane-keeping performance and steering control after the participant had spent a long period on the driving simulator. They presumed that the task helped to counter the vigilance decrement that occurs when attending to a monotonous task for a long period.

In summary, as a main topic of the human factors in driving simulation, distraction, whether internal or external, was mostly found to increase the risk of crashes, even though some studies argued that it has the potential to improve driving performance in vigilance conditions with few critical events.

Cognitive limitations. Another human factor involved in crash simulation is the driver's cognitive limitations. As stated in the discussion on distraction, paying attention to task-irrelevant thoughts impairs driving performance. This is because a human has limited cognitive resources, allocating attention to one could lead to worse perception and reaction to another. Andersen et al. (2011) reported that during a simulated driving task, the detection of a certain change in the environment was worse as the three-dimensional (rather than two-dimensional) distance of that changing stimulus from the driver increased. This implies that attention allocation of drivers is not only determined by how far the object is from the visual focus in terms of the visual angle. Cognitive resources spent on a certain object can also be influenced by depth perception such that even objects located near the center of the visual field can be ignored because they are perceived to be further from the vehicle. In the two driving simulation experiments of Cuenen et al. (2015), the crash occurrence was found to be negatively correlated with attention capacity. Moreover, in their second experiment, cognitive distraction was found to improve performance in lane keeping when the attentional capacity was high and impair performance when the capacity was low, implying a similar interaction to that between the effects of vigilance and a secondary task on driving performance.

Driving a vehicle is in essence multitasking. The driver needs to switch their attention between watching the front and checking the mirrors, as well as turning different functional lights on or off and using his or her foot to manipulate the gas pedal and the brake. By investigating the difference between healthy and brain-injured drivers, Cyr et al. (2009) found a connection between the impairment in dual-task performance and crash rate in high-crash-rate simulated road events. Graefe (2015) focused on the attention deficit in young adults with ADHD (Attention-Deficit/Hyperactivity Disorder) and found that ADHD diagnosis indirectly influenced the variability in lane position through less capability to sustain attention and working memory on the driving task than those without the diagnosis. They also found that failure to stop completely at a stop sign was related to both greater symptoms of inattention and impulsivity symptoms.

To summarize, human drivers can only focus on some areas of the visual field while ignoring other areas. Any factor that impairs the finite cognitive capacity will make this perceptual limitation more severe.

Hazard perception. To avoid a crash, human drivers need to perceive a potentially hazardous event and take anticipatory actions. Hazard perception is described as the ability to detect dangerous traffic scenarios (Horswill and McKenna, 2004). The misperception of a potential hazard is assumed to be related to crash risk. Ba et al. (2016) let participants perform a pre-defined driving task that contained a baseline scenario and a hazard scenario. By comparing those who crashed in the task and those who did not, they found that even though both groups have similar reaction intervals towards the onset of the hazardous event, the no-crash drivers showed anticipatory body reactions (indicated by aroused electrodermal activity) which were followed by more successful actions towards the hazardous event. They concluded that the ability of perceiving risks of crashes is critical for crash avoidance. Borowsky et al. (2016) introduced visual interruption (secondary task) in a simulated driving task in which participants navigated different hazardous scenarios. The result showed that having this interruption during the perception of a hazard impairs the processing of the corresponding information and causes a delay to the actions following the hazard perception, which indicates the resource-consuming nature of hazard perception.

In addition to a secondary interruptive task, the environment in which the hazardous event takes place (pre-crash scenarios) influences the efficiency and accuracy of hazard perception. Yan et al. (2007) used a simulation experiment and found that higher traffic speed can make gap acceptance – evaluation of how risky it is to cross or merge into the major road based on the perception of distances and speeds of the vehicles involved – become more liberal or risky. Edquist et al. (2012) and Yan et al. (2014) found that drivers adopt compensatory driving strategies in more complex pre-crash scenarios (more on-street parking and foggy weather, respectively). However, in both studies, the compensatory actions were not adequate for effective hazard avoidance, implying a negative influence of an overloaded working memory on hazard perception. Michaels et al. (2017) further compared scenarios that caused low, moderate and high mental workload and found that moderate scenario complexity is the most useful in testing individual differences in driving performance because it avoids overloading working memory and making the driver under aroused.

In short, the ability of hazard perception is highly related to one's cognitive ability and is critical for crash avoidance. Pre-crash scenario can influence the efficiency and quality of hazard perception by modulating the cognitive workload.

Risk factors. There are also some risk factors related to impaired driving performance and risky driving behaviors. Stress, especially time pressure, is one contributing factor to crashes. Paschalidis et al. (2018) and Pawar & Velaga (2021) both found the connection between time pressure and risky driving behaviors by using time pressure as a within-subject manipulation. Paschalidis et al. reported that as time pressure increases, gap acceptance becomes more liberal. In Pawar & Velaga's study, the drivers who were under higher time pressure were more likely to make risky decisions and had a higher likelihood of crashes. Another risk factor is fatigue. Passive fatigue is caused when the cognitive workload is low, and a high cognitive workload leads to active fatigue. Saxby et al. (2013) investigated the subjective and objective effects of both forms of fatigue in a driving simulator study. They found that although both forms caused unpleasant subjective experiences, active fatigue was more related to distress and increased coping efforts, whereas passive fatigue is related to a decline in task engagement. With regard to driving performance, only passive fatigue had a negative effect on overall alertness and increased crash probability.

Sleepiness can be regarded as an extreme form of fatigue. Williamson et al. (2014) used prompt questions or asked participants to report at the moment during which they felt sleepy. Result showed that in the next few minutes following the report of sleepiness, crash rate increased by four times compared to other moments during the task. Alcohol consumption which can cause a similar effect to fatigue is also regarded as a major risky factor. Both Yadav & Velaga (2019) and Yadav & Velaga (2020) investigated the effect of Blood Alcohol Concentrations (BAC). Yadav & Velaga (2019) found that the reaction time to crossing pedestrians was largely increased by a higher BAC level. Yadav & Velaga (2020) focused on other aspects of driving behaviors and reported that driving speed and crash probability were both increased by a higher BAC level. In a word, although most risky factors were found to negatively influence driving performance and safety, their way of modulating driving behavior varies.

Generalizability of simulated driving results to naturalistic driving. Although previous research using driving simulators has obtained fruitful findings, a critical issue – whether driving behaviors in a driving simulator resemble those in a naturalistic scenario – is still debatable. Maxwell et al. (2021) reported that behaviors in a driving simulator showed similar patterns to those observed in on-road driving and that the behavioral differences caused by gender and age were also elicited by the driving simulator. They concluded that simulators have the potential to support driver assessment. Charlton and Starkey (2011) found that the automatic form of driving, which has been observed in on-road driving after repetitive experience, was observed in a driving simulator after 12 weeks of testing, which also supports the consistency between driving behaviors in a simulator and naturalistic driving.

However, there is opposing evidence against this consistency. Zöller et al. (2015) focused on braking behaviors in different conditions of the braking system. Behaviors in real vehicles and those in a simulator were compared. Although drivers reacted differently to different braking conditions in a real vehicle, this difference was not found in a simulator. They concluded that static driving simulators have poor validity as to elicit behavioral differences in braking, which could be due to the lack of vestibular feedback. Reed-Jones et al. (2007) found that the application of galvanic vestibular stimulation improved driving performance and decreased simulator adaptation syndrome. This finding is consistent with the conclusion of Zöller et al. Wijayaratna et al. (2019) reviewed studies on how mobile phone distraction affects driving from both simulator research and naturalistic investigation. In simulator studies, the distraction by mobile phone consistently delayed the driver's reaction time. However, some naturalistic studies found that mobile phone distraction had no effect or improved driving performance. Wijayaratna et al. concluded that this dissociation is a result of methodological differences rather than low validity of in-lab simulator-based studies. Factors, such as self-regulation (whether using a cell phone is voluntary or required), arousal (drowsiness and fatigue in naturalistic driving vs. concentration in the lab), can lead to different types of effects in simulator and natural driving studies that are not necessarily related to the validity of simulator-based studies.

Summary. Most of the safety issues regarding human drivers revolve around attention. Some relate to the level of arousal, and attentional resources available to the driver, whereas others relate to direction of attention to the driving task as opposed to other tasks or thoughts. These attentional issues are going to be most problematic in situations that require complex decisions and coordination with other traffic, as is the case in navigating roundabouts. Design considerations to be incorporated into vehicle simulations include methods to restrict a driver's speed appropriately, signal to the driver the presence of other vehicles, and otherwise direct the driver's attention to critical roadway signage.

6. Integration/vision/future work

This paper reviewed the state-of-the-art traffic crash related research from three main areas: crash report analysis, simulation method, and human behavior. The review highlighted the main components that need to be incorporated into future research. Our personal goal is to develop an all-in-one/one step crash analysis system, in which the crash configuration (e.g., information collection, processing and analysis), crash reconstruction and simulation, and crash support information integration and analysis (e.g., human factors), can be integrated and leveraged into the future proposed system. Prior studies have investigated how to automatically develop driving simulation scenarios from crash reports by analyzing crash characteristics. Bobermin and Ferreira (2021) proposed a framework to automatically generate driving simulation scenarios for dangerous curves from police records. Clustering methods were used to discover representative curve crash scenarios by analyzing police records of the crash. The crashes were classified into four clusters that represent four types of typical curve accidents. Curve characteristics of each cluster could be used for driving simulator studies. A study investigated National Motor Vehicle Crash Causation Survey and summarized crashes resulting from teenagers into four types by examining the critical reasons leading to the crash (McDonald et al., 2012). Another study developed representative pedestrian crash scenarios, which could be used for driving simulation studies (Chrysler et al., 2015). Several factors were taken into consideration, such as pedestrian trajectory, behavior, speed and road characteristics. These show a good starting point for further structured integration of crash data sources, different types of simulations (i.e., vehicle simulation, driving simulation, and traffic simulation), and human factors into one framework that can be used to evaluate traffic safety for given contexts of scenarios.

Crash configuration. Leledakis et al. (2021) presented a method for predicting typical crash configurations in vehicles with consideration of the influence of crash-avoiding technologies in the crashworthiness evaluation (i.e., the degree to which a vehicle will protect its occupants from the impacts of accidents). Treatment pre-crash model-in-the-loop simulations were leveraged to predict and evaluate the effect of a conceptual Autonomous Emergency Braking (AEB) system on crash configuration distributions in a feasibility study. The treatment simulations indicated a distinction between the crashes from available real-world databases and expected future crashes. The results showed that a significant number of crashes that were not avoided need further improvement of occupant protection systems. Specifically, it was found the conceptual AEB system shifted many crashes closer to the corner of vehicles for straight crossing path type of crashes. Therefore, there is an urgent need for new setups for assessment of occupant in-crash protection.

The results also showed that many future crashes could be classified into a reduced number of categories. The proposed method can be further leveraged to reduce the complexity of crash types for better managing and evaluating well-defined test cases for crashworthiness. Meanwhile, the diversity and representativity of real-world crashes were maintained.

Crash reconstruction. Crash scene reconstruction has been regarded as one of the key solutions for forensic analysis or traffic incidents research investigation (Kolla et al., 2022). It also helps prevent evidence loss and mitigate economic losses by collecting and cataloging the traffic scenes (FARO Technologies, 2022). FARO has developed software for crash reconstruction to determine the cause of a crash. Firstly, the roadway and texture are drawn in the simulation environment. Then, the momentum system is created to simulate the momentum of the vehicle based on the input speed. The software can also be incorporated with any exact vehicle models and Google map for simulation of actual driving scenarios. As a result, a 20-page crash report is generated through the momentum analysis, including impact velocity, separation velocity, and separation yaw rate. The software is versatile in different crash configurations and simulating damages caused by the crash. The 3D crash reconstruction technology is essential in forensic investigation, crime and fire investigation, and courtroom presentation. It can benefit forensic experts and investigators with the mimic 3D reconstruction of the crash scene, accurate statistical analysis, and courtroom–ready reports (FARO Technologies, 2022). Recently, FARO also integrated the technology with point cloud data from drones and laser scanners to capture accurate and complete 3D images of any environment and objects at the crash scene and fulfill the automation on 3D reconstruction.

Development of automated driving simulation process. Similarly, several studies have integrated microscopic traffic simulation software and driving simulator software to provide more accurate road and traffic flow design for driving simulator studies. The summary of related studies is listed in Table 2. That and Casas (2011) combined microscopic traffic simulation software AIMSUN (Casas et al., 2010) and driving simulator software Simulateur de Conduite Automobile Normalise en Reseau or Simulator for Cooperative Automotive NetwoRk (SCANeR) (Blana, 1996). The traffic simulator AIMSUN simulated the road network and the driving simulator SCANeR controlled drivers' real-time interaction with the traffic flow. The RoadXML file was used to import the road network from AIMSUN into SCANeR. Punzo and Ciuffo (2011) also integrated microscopic traffic simulation AIMSUN and

Table 2
Studies integrating microscopic traffic simulation and driving simulation.

Reference	Microscopic traffic simulation platform	Driving simulation / 3D graphic engine platform	Additional information
(That and Casas, 2011)	AIMSUN	SCANeR	
(Punzo and Ciuffo, 2011)	AIMSUN	SCANeR	
(Sun et al., 2015)	VISSIM 5.40	VIRTOOLS 5.0	This platform supports multiple users.
(Biurrun-Quel et al., 2017)	SUMO	Unity 3D	
(Barthauer and Hafner, 2018)	SUMO	SILAB	
(Miller et al., 2020)	VISSIM	Unity 3D	This platform supports multi-modal and multi-user.

driving simulator SCANeR. The integrated platform was tested on a 6.5 km road. Sun et al. (2015) developed a traffic simulator with multiple driving simulators (TSMDS) platform which allowed multiple drivers to drive in the virtual environment simultaneously. The TCP / IP network protocol was used to transfer data between the two systems. The microscopic traffic simulation VISSIM 5.40 and driving simulator VIRTOOLS were selected to test the proposed platform. In addition, a driving simulation experiment involving 27 drivers was conducted using the developed platform and drivers' responses were consistent with the field observation which validated the proposed platform. Biurrun-Quel et al. (2017) developed a driving simulator including two parts, which were microscopic traffic simulation part and 3D graphic engine part, respectively. The Simulation of Urban Mobility (SUMO) (Krajzewicz et al., 2002) was selected as the microscopic traffic simulation platform to generate the traffic flow and road. The Unity 3D was selected as the 3D graphic engine. TraCI, which is an API of the SUMO simulation, was used as the communication between Unity 3D and SUMO. The SUMO and driving simulation software SILAB were integrated to develop a driving simulation which can transfer surrounding traffic and signal control from SUMO into SILAB (Barthauer and Hafner, 2018). A platform was developed integrating traffic simulation SUMO and 3D graphic engine Unity 3D which support multi-modal and multi-user traffic simulation (Miller et al., 2020). For example, a driver using a car rig can control the car displaying in multiple screens and meanwhile another person can ride a bicycle with bicycle rig and movement of bicycle pedal is projected in virtual world to control the bicycle in the VR environment.

7. Conclusions

In search of factors that can contribute to traffic safety in a mixed traffic with connected and autonomous vehicles (CAVs), it was found that human behavior and road infrastructure prevail and must be considered together with the traffic itself. For example, roundabout is one of the important traffic environments that presents challenges to human drivers and CAVs. Because crashes in simulated and actual driving occur infrequently for individual drivers, vehicle crash simulations provide an avenue for studying issues of mixed traffic (e.g., at roundabouts). Crash reports involving human-driven vehicles offer useful input for determining the scenarios and conditions under which crashes are likely to occur. Sophisticated methods exist for analyzing crash reports to provide input for the crash simulations. Methods exist for conducting crash simulations that allow manipulation of various parameters related to vehicle design and conflict situations that may lead to crashes. The most likely scenarios for crashes in specific road infrastructure environment (e.g., roundabouts) can be determined and simulated. Driving simulators in which humans perform driving tasks in various contexts can provide knowledge about the human factors that need to be considered, which center around the drivers' limited attention capacity. This knowledge can be used as input to vehicle simulations to provide a full, contextualized analysis of likely crash scenarios and ways in which crashes could be avoided by knowing human drivers' tendencies. These tendencies can be incorporated into the interaction protocols for CAVs and humans with the goal of increasing safety. Therefore, in this paper, we comprehensively reviewed the crash-related research including crash report analysis, simulation method, and human behavior; this review set research goals and provided the research resources for further crash analysis implementation in the safety domain.

8. Contributions to the body of knowledge

This study contributes to the body of knowledge by reviewing recent literature in the traffic safety realm for supporting futuristic transportation infrastructure settings with connected and autonomous vehicles. The review was conducted based on the authors' view that the comprehensive analysis of futuristic transportation safety requires an integrated framework with traffic crash data source, simulation methods, and human factors. The state of the art in these three related aspects and research gap in integrating them were identified. This can be used to guide future research to push for a safer transportation infrastructure in the mixed traffic with CAVs.

CRediT authorship contribution statement

Ran Ren: Writing – original draft, Writing – review & editing. **Hang Li:** Writing – original draft, Writing – review & editing. **Tianfang Han:** Writing – original draft, Writing – review & editing. **Chi Tian:** Writing – original draft, Writing – review & editing. **Cong Zhang:** Writing – original draft, Writing – review & editing. **Jiansong Zhang:** Conceptualization, Writing – original draft, Writing – review & editing, Funding acquisition. **Robert W. Proctor:** Conceptualization, Writing – original draft, Writing – review & editing, Supervision, Funding acquisition, Project administration. **Yunfeng Chen:** Conceptualization, Writing – original draft, Writing – review & editing, Funding acquisition. **Yiheng Feng:** Conceptualization, Writing – original draft, Writing – review & editing, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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